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Risk constrained self-scheduling of hydro/wind units for short term electricity markets considering intermittency and uncertainty

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ABSTRACT

In view of the intermittency and uncertainty associated with both the electricity production sector of restructured power system and their competitive markets, it is necessary to develop an appropriate risk managing scheme. So that it is desirable to trade-off between optimum utilization of intermittent generation resources (i.e. renewable energy resources), uncertain market prices and related risks in order to maximize participants' benefits and minimize the corresponding risks in the multi-product market environment. The main goal of this paper is to investigate risk management by introducing a novel multi-risk index to quantify expected downside risk (EDR) which is caused by both the wind power and market price uncertainties. Value-at-Risk (VaR) method is used to assess the mentioned risk issue by the proposed weighted EDR, so that an optimal trade-off between the profit and risk is made for the system operations. Also, the roulette wheel mechanism is employed for random market price scenario generation wherein the stochastic procedure is converted into its respective deterministic equivalents. Moreover, the autoregressive integrated moving average (ARIMA) model is employed to characterize the stochastic wind farm (WF) generation by predetermined mean level and standard deviation of wind behavior as well as temporal correlation. The problem is formulated as a mixed-integer stochastic framework for a hydro-wind power system scheduling and tested on a generation company (GENCO).

Contents

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1. Introduction

Emergence of electric utility deregulation issues, recent liberalization of the electricity markets in several countries and striking growth of wind power application has increased the need for risk measurement and management tools. Risk in economic theory is defined as an option where the profit is not known because of different uncertain parameters, such as market price and generating units' uncertainties, but for which an array of alternative outcomes and associated probabilities are known [1]. The price uncertainty is one key factor which can change the value of energy trades in different market conditions. A firm's portfolio risk is discussed by evaluating the risk venture from changes in any of the variables that affect existing contracts or the firm's projections from demand, supply and prices [2]. Value at-Risk (VaR) is a well-known measure which is applied in many risk-management studies, especially the electricity market activities with varying objectives, including [3]: (i) avoiding great profit losses due to the price fluctuations or energy consumption uncertainty which their risks are not accurately reported or have not been properly controlled; (ii) proper modeling and risk quantification for intermittency of traditional generating units as well as the uncertainty of renewable energy resources, e.g. wind power, solar energy, and biomass; and (iii) identifying optimal hedging strategies or assessing hybrid hedging opportunities in order to control the financial risks of GENCOs as cost effectively as possible. With the use of VaR method, a market operator and participants can then determine the best use of the physical and financial capital costs in order to maximize their earnings [4] or perform comprehensive risk management in view of both the portfolio and operational risk [5].

An integrated risk management cost is proposed in [6] for simultaneous analysis on both uncertainties of spot prices and production. This work presents an efficient market model which allows power producers to identify a benchmark value for a forward contract. This value is equal to the sum of the expected production marginal cost and the spread option embedded in the spot selling. Another risk management model is introduced and carried out in [7] to provide the proper trade-off between the maximum profit and the minimum risk of electricity price and the technical features of hydrothermal units for GENCOs in for day-ahead competitive market. Ref. [8] has proposed a stochastic mid-term risk-constrained hydrothermal scheduling algorithm to maximize the profit of GENCO. In this work, the profit shortfall of each scenario is defined as the risk of scenario. In [9] the financial risk is considered in the stochastic Price-Based Unit Commitment (PBUC) problem.

Under deregulation, there are many uncertainties in the power system related to, e.g., electrical demand and price variations and generator and branch outages. In [10,11], a Unit Commitment (UC) problem is implemented for the stochastic security-constrained electricity market clearing problem to determine reserve services considering the expected load not served. Ref. [12] considers two modeling approaches for the reduction of computational effort of the stochastic UC. In these studies, the generation outages considered as a load increments. A multi-stage stochastic program has been proposed in [13] for self-scheduling of a thermal unit considering the price uncertainty.

It is noted that the intermittency of traditional generation unit and uncertainty of renewable resources as well as demand side uncertainty have been investigated apart from the market price risk in several surveys. For instance, in [14] the stochastic SCUC and Monte Carlo simulation method has been used for contingencies of generation units and transmission lines and load forecasting inaccuracies. Also, [15] has considered the effects of the stochastic wind speed and load on the UC and economic dispatch of power systems with high levels of wind power. Results of this stochastic optimization problem show less costly and better scheduling of resources than the deterministic optimization.

This paper addresses a risk constrained market model for the hybrid wind-hydro power scheduling (WHPS) problem by a GENCO. This risk constrained short-term operation model is applied by GENCO to determine the commitment status and power generation of each hydro unit and achieve optimal trade-off between the maximum profit and risks of the price as well as wind power behavior uncertainties. The proposed model is formulated as a stochastic optimization problem wherein the expected profit is maximized using the mixed integer programming (MIP) technique. The price uncertainty is modeled based on the price forecast error using the roulette wheel mechanism to generate price of energy and spinning and non-spinning reserves for each hour of the scheduling period. The contributions of this paper with respect to the previous works in the area can be briefly summarized as follows:

(i) Risk of generating units' intermittency as well as the price and wind power generation uncertainties is modeled in the stochastic optimization framework.
(ii) New multi-risk index is presented to quantify maximum expected downside risk of the electricity market and system uncertainties.

The remainder of this paper is organized as follows: Section 2 describes the stochastic formulation of hybrid wind-hydro scheduling. The ARIMA method for modeling of wind power generation uncertainty is explained in Section 3. Section 4 introduces the concept of VaR in risk measurement and presents the proposed risk management model for WHPS problem. Section 5 addresses the case studies, simulation assumptions and provides results with detailed discussions. In Section 6, some relevant conclusions are addressed.

2. MIP formulation of WHPS

In the following subsections, the optimization problem of WHPS is introduced in the form of MIP formulation.

2.1. Objective function

The objective function of our proposed WHPS problem is profit maximization which can be written as follows:

$$PROFIT^{total} = \pi^b(t)p^b(t) + \sum_s p^{norm}(s) \cdot PROFIT(s) \tag{1}$$

$$PROFIT(s) = \sum_{t \in T} \left\{ \pi^{sp}(t,s)p^{sp}(t,s) + \sum_{j \in J} \{\pi^{sr}(t)R(j,t,s) + \pi^{ns}(t,s)\{N_u(j,t,s) + N_d(j,t,s)\}\} - \sum_{j \in J} A_j y(j,t,s) \right\} \tag{2}$$

where $PROFIT^{total}$ is the objective function of the optimization problem and it is equal to the fix revenue from bilateral contract in

Nomenclature

Sets and indices

j	Hydro unit index
wf	Wind farm index
t	Time interval (h) index
s	Scenario index
u	Uncertain parameter index
J	Hydro units
WF	Wind farms
N	Set of indices of blocks of piecewise linearization of hydro unit performance curve
T	The periods of market time horizon (h)
S	Scenario numbers
SP	Stochastic parameters (*wf* indicates wind farms and *price* refers to uncertain market price)
i, p, q, r	Sets of ARIMA family model
N	Time number of wind power generation time series

Constants

$\pi^b(t)$	Bilateral contract price ($/MWh)
$\pi^{sp}(t,s)$	Market price for energy transaction ($/MW h)
$\pi^{sr}(t,s)$	Market price for spinning reserve ($/MW h)
$\pi^{ns}(t,s)$	Market price for non-spinning reserve ($/MW h)
η	Conversion factor equal to 3.6×10^{-3}(H m^3 s/m^3 h) (1 H m^3=10^6 m^3)
Θ	Number of periods of the planning horizon (24 h)
τ_{km}	Time delay between reservoirs of hydro units k, m (h)
A_j	Start-up cost of unit j ($)
$b_n(j)$	Slope of the volume block n of the reservoir associated to unit j (m^3/s/H m^3)
$b_n^k(j)$	Slope of the block n of the performance curve k of unit j (MW/m^3/s)
$F(j,t,s)$	Forecasted natural water inflow of the reservoir associated to unit j (H m^3/h)
L	Number of performance curves
M	Number of prohibited operating zones
NS	Number of scenario after scenario reduction
$p^b(t)$	Power capacity of bilateral contract (MW)
$p(s)$	Probability of scenario s
$p^{norm}(s)$	Normalized probability of selected scenario s
$\underline{Q}(j)$, $\overline{Q}(j)$	Minimum and maximum water discharge of unit j (m^3/s)
$\nu_0(j)$	Minimum content of the reservoir associated to unit j (H m^3)
$\nu^0(j)$, $\nu^\Theta(j)$	Reservoir content at the beginning and end of the study period (H m^3)
$\nu_n(j)$	Maximum content of the reservoir j associated to nth performance curve (H m^3)
EDR^{max}	Maximum value of the acceptable downside risk tolerance
ω_{sp}	Risk weights of stochastic parameters
α	Maximum value of profit loss tolerance

Variables

$\psi_n(j,t,s)$	Volume of block n for the reservoir of unit j (H m^3)
$N_d(j,t,s)$, $N_u(j,t,s)$	Non-spinning reserve of a unit j in the spot market when unit is off and on, respectively (MW)
$p^{sp}(t,s)$	Power for bid on spot market (MW)
$PROFI(s)$	Profit of scenario s
$PROFIT^{total}$	Objective function
$Q(j,t,s)$, $q_n(j,t,s)$	Water discharge of unit j and block n (m^3/s)
$R(j,t,s)$	Spinning reserve of hydro unit j in the spot market (MW)
$sp(j,t,s)$	Spillage of the reservoir associated with unit j (m^3/s)
$\nu(j,t,s)$	Water content of the reservoir associated with unit j (H m^3)
$TARGET_{profit}$	Target profit
$RISK(s)$	Downside risk for scenario s
$PROFIT(s)$	Profit in scenario s ($)
$E[\,]$	Expected value
D^i	Back shifter
θ_0	Deterministic trend
$W(t)$	Square root of wind power output
$WP(t)$	Wind power output

Binary variables

$\beta_n(j,t,s)$	1 if volume of reservoir water is greater than $\nu_n(j)$
$y(j,t,s)$	1 if jth hydro unit is started-up
$I(j,t,s)$	Binary variable of jth hydro unit operation state

addition to the expected profit over scenarios. Variable profit of each scenario consists of the sale of energy and reserves in the spot market by hydro units. The last term of profit function refers to the corresponding cost of hydro units regarding their start-up cost [16]. It is noted that, to decrease the risk of the price volatility or unsuccessful contribution in the spot markets, GENCOs participate in bilateral contracts and their remaining capacity will be sold on the spot market [17].

The WHPS model is subject to the equality and inequality constraints. The power balance equation is the main constraint of this problem which means that the total generated power of hydro units and WFs should be equal to the total power sold in the spot market and bilateral contract for each time and each scenario as follows:

$$\sum_{j\in J} p(j,t,s)+\sum_{wf\in WF} p(wf,t,s)\geq \sum_{n=1}^{NB} p_m^b(t)+p^{sp}(t,s)\quad \forall t\in T,\ \forall s\in S \tag{3}$$

The other constraints of hydro units in the WHPS problem are addressed in the following subsection.

2.2. Hydro units' model

Fig. 1 shows the relationship between the generated power, water discharge, and multi performance curves of hydro units. Hydro units can be connected in series or parallel. The start-up costs of hydro units are considered in the model to prevent unnecessary commitments, loss of water during start-up period, wear and tear of the windings and mechanical equipment, and malfunctions in the control equipments [16]. For the sake of more accuracy, multi performance curves are used because this concept is very important when storage capacity of reservoirs is small and the generated power is dependent of hydro unit head. In the following formulations, L is the number of the performance curves for hydro units. The higher value of L refers to the more accuracy of the model.

2.2.1. Linear formulations for volume and multi performance curves

The linear formulations of hydro power units with L performance curves are as follows:

$$\nu(j,t,s)\geq \nu_0(j)\quad \forall j\in J,\ \forall t\in T,\ \forall s\in S \tag{4}$$

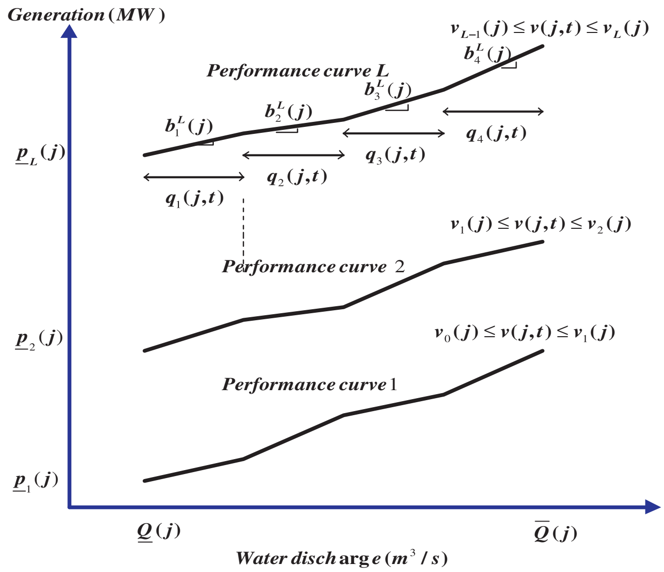

Fig. 1. Piecewise linear non-concave unit performance curves for the hydro unit j.

$$v(j,t,s) \le v_L(j)\beta_{L-1}(j,t,s) + \sum_{n=2}^{L} v_{n-1}(j)[\beta_{n-2}(j,t,s) - \beta_{n-1}(j,t,s)] \quad \forall j \in J,\ \forall t \in T,\ \forall s \in S \tag{5}$$

$$v(j,t,s) \ge v_{L-1}(j)\beta_{L-1}(j,t,s) + \sum_{n=3}^{L} v_{n-2}(j)[\beta_{n-2}(j,t,s) - \beta_{n-1}(j,t,s)] \quad \forall j \in J,\ \forall t \in T,\ \forall s \in S \tag{6}$$

$$\beta_1(j,t,s) \ge \beta_2(j,t,s) \ge \cdots \ge \beta_{L-1}(j,t,s) \quad \forall j \in J,\ \forall t \in T,\ \forall s \in S \tag{7}$$

The Eqs. (4)–(7), determines the performance curves based on the water volume. $\beta_n(j,t,s)$ is a binary variable; equals to 1 when water volume of the reservoir is greater than $v_n(j)$. In other words, these equations choose the right curve for head according to the content level.

2.2.2. Linear power-discharge performance curves

After determination of each unit in this subsection, the linear relationship between the generated powers and the discharged water for corresponding performance curve can be presented as

$$p(j,t,s) - \underline{p}_k(j)I(j,t,s) - \sum_{n \in N} q_n(j,t,s)b_n^k(j) - \overline{p}(j)[(k-1) - \sum_{n=1}^{k-1}\beta_n(j,t,s) + \sum_{n=k}^{L-1}\beta_n(j,t,s)] \le 0 \quad \forall j \in J,\ \forall t \in T,\ \forall s \in S,\ 1 \le k \le L \tag{8}$$

$$p(j,t,s) - \underline{p}_k(j)I(j,t,s) - \sum_{n \in N} q_n(j,t,s)b_n^k(j) + \overline{p}(j)[(k-1) - \sum_{n=1}^{k-1}\beta_n(j,t,s) + \sum_{n=k}^{L-1}\beta_n(j,t,s)] \ge 0 \quad \forall j \in J,\ \forall t \in T,\ \forall s \in S,\ 1 \le k \le L \tag{9}$$

where $p(j,t,s)$ is the generated power by the hydro unit j at hour t, $\underline{p}_k(j)$ is the minimum power generation of the head k which is determined by $\beta_n(j,t,s)$. Also, $\overline{p}(j)$ is the capacity of hydro unit j, and $q_n(j,t,s)$ is the water discharge of the block n. Finally, $b_n^k(j)$ is the slope of the block n of the variable head k of hydro unit j.

2.2.3. Water discharge limits

The water discharge limit and initial and final volume and water balance equation is same as the equations presented in [18]; however, in the proposed WHPS model the spillage effect is also considered which is inspired by [19].

3. Uncertainties characterization

In order to have a profitable participation in the electricity markets, the GENCOs are inevitably supposed to consider different types of uncertainty sources in their self-scheduling. The sources of uncertainty for short term WHPS problem are generating units' contingency, specially wind power generation, and price variations. To solve the stochastic WHPS problem, a two-stage solution method is proposed in this paper. In the first stage the multiperiod scenarios are generated. In this stage, the Monte Carlo Simulation (MCS) method and the roulette wheel mechanism are used to model price uncertainty. Also, in order to incorporate the stochastic behavior of the wind power generation in the first stage, the ARIMA model based on the time series approach is implemented. Besides, a scenario reduction technique is also presented in the paper to reduce the computation burden of the proposed stochastic procedure. In the second stage, the optimization problem of each generated scenario (by the scenario reduction technique) is modeled and solved in the form of a MIP problem.

3.1. Wind power uncertainty modeling

The high penetration level of wind power in the electric power system calls for new approaches and simulation tools that can help electric utilities to analyze the impact of the stochastic behavior of the wind generation [20–23]. The wind power generation (WPG) increases as the cube of wind speed. Therefore, the wind speed forecast and related errors in this field is the key parameter in the investigation of the wind power uncertainty. Existing approaches for the stochastic modeling of the WPG which are discussed in references can be classified into two main categories: wind speed-based approaches [21–26], and wind power-based approach [27]. Wind speed-based approach requires the wind speed measurements and an accurate wind farm model which is usually unavailable. On the other hand, noticeable error in the application of wind speed-based approaches is the main concerns that system operator faces with them, e.g. of 3%, in wind speed modeling may cause an error of around 27% in wind power. This is because, as mentioned above, wind power varies with the cube of the wind speed while the speed is between the cut-in and rated value of wind speed. The accurate wind farm model is not needed in the wind power-based approach where wind power measurements are available. In fact, electric utilities measure and record wind power flows into their networks. Thus, they have direct access to these wind power data. In this case, wind power measurements can be directly used to build a wind power model. In addition, the need for wind speed measurements is alleviated.

In this paper, an Auto-Regressive Integrated Moving Average (ARIMA) process is used to model wind power generation uncertainty directly as a wind power-based stochastic approach. Detailed explanation of the ARIMA process is presented in next subsection.

3.1.1. ARIMA model of wind power

An $ARIMA(p,d,q)$ model of the non-stationary random process $W(t)$ is depicted as [30]

$$\left(1 - \sum_{i=1}^{p}\varphi_i D^i\right)(1-D)^r W(t) = \theta_0 + \left(1 - \sum_{i=1}^{q}\theta_i D^i\right)n(t) \tag{19}$$

where θ_i is the moving average (MA) coefficients; φ_i is the Auto-Regressive (AR) coefficients; $n(t)$ is a white Gaussian process with zero mean and variance σ_n^2; θ_0 refers to the deterministic trend term when $r>0$. In the case of $d=0$, the *ARIMA*(p,d,q) model is reduced to an *ARMA*(p,q) model. The *ARMA*(p,q) model is reduced to a *AR*(p) model when $q=0$, and a *MA*(p) model when $p=0$. The coefficients of the *ARIMA* model can be estimated by different approaches, e.g. the Yule-Walker estimator, the least square estimator, and the maximum likelihood estimator [28]. It should be noted that there are two model selection criteria for determination of ARIMA's family in various stochastic analysis. The common selection criteria are Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC). The AIC of the ARIMA has been defined in [28]. Based on the results of [27], the ARIMA(0,1,1) model can be shown as (20). This model is well-suited for the wind power time series. Hence, ARIMA(0,1,1) model is considered in this work to generate different wind power generation scenarios and model random trend of the wind farm activities in the proposed hybrid wind-hydro power scheduling.

$$\begin{cases} (1-D)W_0(t)=(1-\theta_1 D)a(t) \\ WP(t)=W_0^2(t) \end{cases} \quad \text{for } t=1,\ldots,N \tag{20}$$

Due to the physical limitations of the wind farm, the WPG is bounded within cut-in and rated value speeds. However, the ARIMA model cannot consider these limitations. For this reason the limited ARIMA (LARIMA) model is obtained by introducing a limitations for the standard ARIMA model to include the upper and lower bounds of the WPG. A limiting operation is introduced on $W_0(t)$ as

$$W_0(t)=\begin{cases} W_{max}, & W_0(t)>W_{max} \\ W_0(t), & W_{min}<W_0(t)<W_{max} \\ W_{min}, & W_0(t)<W_{min} \end{cases} \tag{21}$$

where W_{max} and W_{min} denote the upper and lower bounds of the square root of the wind power output, respectively. The block diagram of the limited ARIMA(0,1,1) is shown in Fig. 2.

3.2. Price uncertainty modeling

In this work, the price uncertainty is considered based on the price forecast error. Firstly, the probability distribution function of the system price forecast error should be constructed. Fig. 3 shows an example of the continuous distribution function of the price forecast error along with its discretization. Here, seven intervals are centered on the zero mean and each of the intervals is one price forecast error standard deviation (σ) wide, as done in [29,30]. On the basis of the different price forecast levels and their probabilities obtained from the probability distribution function, the roulette wheel mechanism [30] is implemented to generate scenarios for each hour. For this purpose, at first, the probabilities of different price forecast levels are normalized such that their summation becomes equal to unity. Then the range of [0, 1] is occupied by the normalized probabilities as shown in Fig. 4. After that, random numbers are generated between [0 and 1]. Each random number falls in the normalized probability range of a price forecast level in the roulette wheel. That price forecast level is selected by the roulette wheel mechanism for each hour and scenario. A higher number of the scenarios results in the better modeling of the uncertainties but with the cost of higher computation burden. Accordingly, scenario reduction techniques can be employed to reduce the number of scenarios while maintaining a good approximation of the system uncertain behavior. In this paper, the basic idea of scenario reduction is to eliminate a scenario with very low probability and scenarios that are very similar [29]. Based on this approach the most probable and dissimilar scenarios can be extracted (NS scenarios) for using in the stochastic risk constrained WHPS problem.

4. Risk model for HWPS integration

Considering uncertain parameters of restructured power systems and their competitive market such as traditional generation units intermittencies, uncertainty of renewable DG, uncertain market price and demand side uncertainty, electricity market participants especially GENCOs are encountered with different risks. Hence, GENCOs need to reformulate the portfolio formulations as the risk-constrained optimization problem in order to trade-off between the maximum profit and minimum risk of the uncertain parameters' impacts. Main risk categories which are

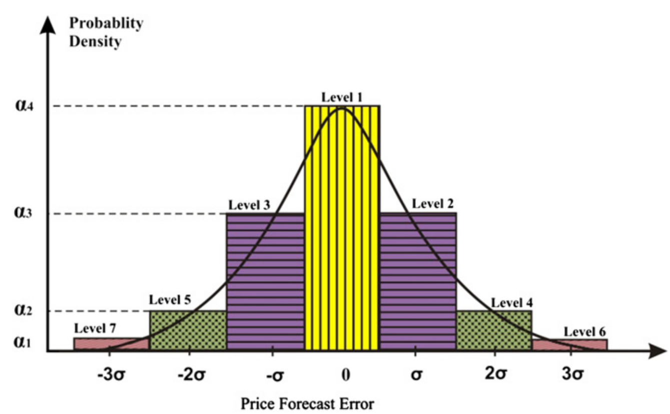

Fig. 3. Typical discretization of the PDF of the price forecast error [30].

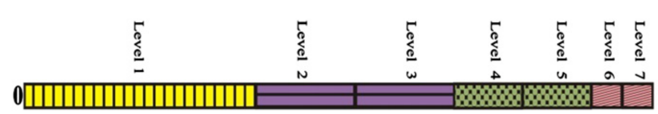

Fig. 4. Roulette wheel mechanism for the normalized probabilities of the price forecast levels [30].

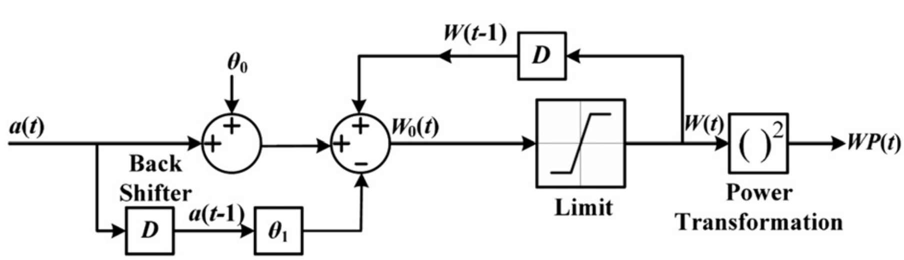

Fig. 2. Block diagram of the limited ARIMA(0,1,1) [30].

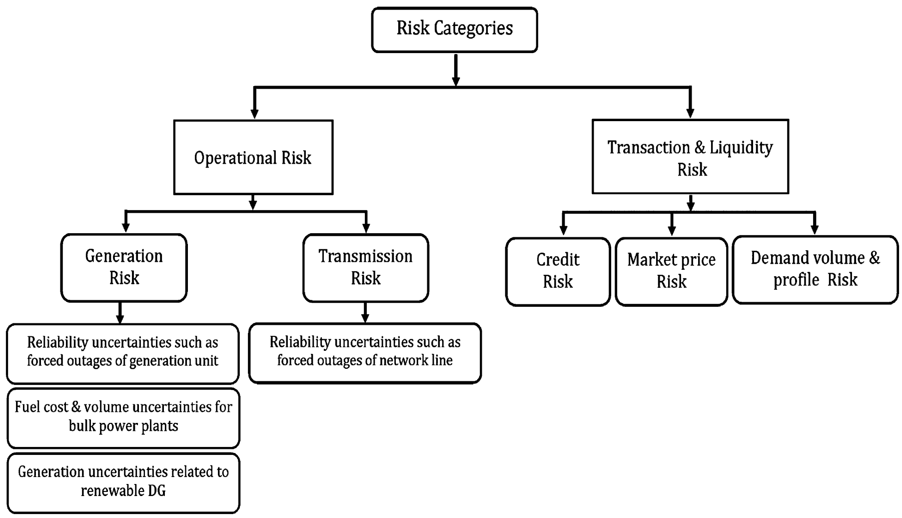

Fig. 5. Different risk categories.

discussed in risk management reports can be classified into two main groups as depicted in Fig. 5.

This paper addresses a risk of the market price and wind power generation uncertainties and proposes a new market model to hybrid wind-hydro power scheduling for a GENCO. This risk constrained short-term operation model is applied by a GENCO to determine the status of commitment and power generation of each hydro unit, optimum bidding strategy of the wind farm generations.

4.1. Risk measurement and risk-constrained management

Risk measurement is generally quantified with the use of "Value at-Risk" concept. The financial industry was the pioneer to apply the VaR in order to provide quantification for a company portfolio exposure to the risk. In particular, this measure of risk summarizes the expected maximum loss over a target horizon within a determined confidence interval [31,32]. The VaR includes any risk measure index that can be considered as the risk of the profits under a fixed threshold (the losses above a fixed threshold). Therefore, the VaR can be explained as downside risk measure.

GENCO's owner like any financial industries would set a target profit $TARGET_{profit}$, and the risk associated with its decision is measured by failure to meet the target profit. If the profit for one scenario is larger than the target profit, the associated downside risk would be zero; otherwise, it is the amount of unfulfilled profit. Mathematical expression of this concept of risk measurement is given by (22)

$$RISK(s)=\begin{cases} TARGET_{profit}-PROFIT(s) & \text{if } PROFIT(s)\le TARGET_{profit} \\ 0 & \text{if } PROFIT(s)>TARGET_{profit} \end{cases} \tag{22}$$

The expected downside risk for a retailer is defined as

$$EDR(TARGET_{profit})=E[RISK(s)]=\sum_{s\in S}\rho^{norm}(s)\cdot RISK(s) \tag{23}$$

The smaller value of EDR ($TARGET_{profit}$), the better it is for the GENCO since EDR ($TARGET_{profit}$) represents the profit shortfall at the target profit. If a GENCO is not satisfied with the risk level, a risk constraint could be added to the original formulation as

$$EDR(TARGET_{profit})<EDR^{max} \tag{24}$$

where EDR^{max} is the acceptable downside risk tolerance. In present work, a new multi-target risk index is proposed to determine the target profit and maximum EDR of a GENCO for integrated impacts of uncertain parameters in risk assessment. This novel index is defined based on the average profit of different scenarios related to any risk categories, scenarios probability and weighted coefficients of uncertain parameters which is specified with respect to GENCO's requirements as follow:

$$\begin{gathered} TARGET_{profit}=\sum_{u\in sp}\omega_{sp}\cdot PROFIT_{sp}^{average} \\ EDR^{max}(TARGET_{profit})=\alpha\cdot\sum_{u\in sp}\sum_{s\in S}\omega_{sp}\cdot\rho_{sp}(s)\cdot PROFIT_{sp}(s) \\ \sum_{u\in sp}\omega_{sp}=1 \end{gathered} \tag{25}$$

In Eq. (25), α is the maximum percentage of the profit loss tolerance, ω_{sp} is the desirable weight of each uncertain parameter for risk assessment and ρ_{sp} is the probability of each scenario.

In the present paper, two main categories of power system uncertainties (market price and wind power uncertainties) are considered in risk analysis of daily activities GENCO. Three different states of risk weighting on mentioned uncertain parameters are investigated under two profit loss tolerance (α) which are more detailed in next section.

5. Numerical results

The risk constrained HWPS model developed in Section 3 is applied to a GENCO considering both hydro and wind energy application during day-ahead energy trading market. To model hydro units, eight hydro units are considered. The required data of hydro units are taken from [18]. In addition to hydro units, two wind farms are assumed which are supervised financially under GENCO operating scheme. Random behavior of wind power generation is modeled by ARIMA(0,1,1) time series model as described in Section 3.1. Two wind farms are separately modeled to simulate correlation concerns of the stochastic wind power behavior in different areas of the network. Auto and cross correlation coefficients related to two applied wind farms are considered as Appendix I. As mentioned in Section 3, the proposed risk assessment model includes both uncertainties of wind power and market price. The detailed market prices for energy and capacity price are given in [33]. In this study, a uniform market clearing price is assumed for all buses.

In order to have comprehensive analysis on the stochastic HWPS model, one base case (without risk) and two different risk constrained cases regarding to various profit loss tolerance are simulated

and investigated. In addition, four main simulation cases, three different sub-cases are considered in each risk constrained case based on different importance weighting factors for uncertainties of market price and wind power generation. In this paper, the proposed risk management methodology is programmed in the General Algebraic Modeling System (GAMS) that is a high-level modeling language for mathematical programming and optimization [34]. The PC used in the simulation is a Core2-Due Intel Processor, 2.2 GHz and 4 GB of RAM.

With the use of ARIMA method for modeling the stochastic behavior of wind power generation and roulette wheel mechanism to model uncertainty of energy/reserve market prices, 200 scenarios, including daily wind power time series and daily market price profiles, are generated. Increasing the number of scenarios for the risk assessment model leads to have better modeling of the price/wind uncertainties with the cost of higher computation burden and simulation time. Accordingly, the scenario reduction technique is employed to reduce the number of total generated scenarios (200 daily market price profile/wind power generation scenarios) while maintaining a good approximation of the uncertain behavior of these risk resources. In this paper, the basic idea of scenario reduction is to eliminate scenarios with very low probability and high similarity. Selected scenarios, their normalized probability and total daily power generation of wind farms (generated power by WF1 and WF2) are presented in Table 1.

5.1. Base cases

In order to risk measurement and management for illustrated GENCO, we need to use some basic results as risk reference to investigate the effect of system/market uncertainties on the GENCO economical performance. During the base case, two sub-cases are assumed that model the stochastic trend of day-ahead market activity regarding to price and wind power uncertainties, separately. Detailed assumptions and results of the base case are summarized as follows.

5.1.1. Price uncertainty considering average generation of wind power

In this case the price uncertainty is considered without risk constraints. It should be noted that the average power output of two wind farms is considered as WF's power generation in each scenario.

5.1.2. Wind power uncertainty considering average market price

WHPS problem considering wind power generation uncertainty without risk constraints is carried out in the sub-case B. Analogous to what is noted for the sub-case B, the average value of the market price is assumed. Maximum daily power output of two wind farms is listed in Table 1.

Table 2 shows the profit of each given scenario which is a function of hourly market price/wind power uncertainties, in sub-cases A and B. The GENCO would set its target profit with the use of average value of scenario profits ($PROFIT_k^{avearge}$) and weight coefficients (ω_{sp}) in Eq. (25). According to the results of Table 2, the average profit of each base case is equal to $PROFIT_{Price}^{avearge} =$ \$1356065, $PROFIT_{WP}^{avearge} =$ \$1346408 for sub-cases A and B, respectively. Now, with respect to the profit results of the base cases, i.e. WHPS problem without risk constraint, GENCO is able to re-schedule its day-ahead market operation plan based on different levels of the desired profit loss tolerance (DPLT). Two different cases on profit loss tolerances (α=20% and α=10%) are investigated in this work. It should be pointed out that DPLT implies on allowable value of the profit loss which GENCO can suffer. Moreover, different level of permissible risk, various uncertain parameters of the system and market might have dissimilar importance weighting factor depending on the GENCO purpose and properties. So, in addition to the mentioned main cases, various risk levels of the sub-cases are carried out regarding to the source of uncertainty (Market price and wind power) which is considered as the main purpose of the GENCO.

5.2. Case I: α=20% as the maximum profit loss tolerance

Generation companies as one of the main participants of the competitive electricity market have intended in the present work and a risk constrained model is presented for hybrid hydro-wind generation system scheduling which is owned by a GENCO. Based on the concept of EDR, whatever EDR^{max} value is greater, GENCOs are able to earn more profits similar to market operation without risk constraints. Variation rate of GENCO's profits is analyzed in two allowable expected downside risk indices. During the first case, the proposed risk constrained model is applied with assumption that α=20% as maximum tolerance rate of profit due to risk constraints.

Case I-A: $\omega_{wf} = 1$, $\omega_{price}=0$

This sub-case assumes maximum risk weight for wind power uncertainty, $\omega_{wf}=1$, and EDR^{max} is calculated based on this assumption by Eq. (25). Risk management under this assumption can be applied for those situations that the stochastic behavior of wind power generation is the main target of the risk assessment in GENCO's activities. According to the results of this sub-case, the GENCO will be able to precisely investigate its net income subject to the risk of the generation uncertainty. The results of this case is addressed in Table 3.

Case I-B: $\omega_{wf} = 0$, $\omega_{price}=1$

During sub-case I-B, the risk concerns of uncertain energy/reserve market prices are the main scope of the proposed risk

Table 1
Selected scenarios, their normalized probability and total generation related wind farms.

Scenario number	*Probability (**normalized**)*	*Total wind power (**MW**)*	*Scenario number*	*Probability (**normalized**)*	*Total wind power (**MW**)*
Scenario 1	0.088	2676.4	**Scenario 11**	0.042	2658.8
Scenario 2	0.030	2805.0	**Scenario 12**	0.054	2605.4
Scenario 3	0.033	2907.7	**Scenario 13**	0.021	2729.5
Scenario 4	0.016	2646.6	**Scenario 14**	0.059	2825.5
Scenario 5	0.058	2762.3	**Scenario 15**	0.024	2774.7
Scenario 6	0.071	2570.7	**Scenario 16**	0.061	2742.1
Scenario 7	0.040	2508.7	**Scenario 17**	0.047	2549.9
Scenario 8	0.065	2546.0	**Scenario 18**	0.051	2739.8
Scenario 9	0.075	2585.7	**Scenario 19**	0.056	2787.9
Scenario 10	0.033	2703.6	**Scenario 20**	0.076	2833.3

Table 2
Scenario profit in base cases without risk constraints.

	Base case-A	**Base case-B**		**Base case-A**	**Base case-B**
Scenario 1	1376992	1359744	**Scenario 11**	1542873	1529142
Scenario 2	1542130	1533312	**Scenario 12**	1418935	1403978
Scenario 3	1574088	1564326	**Scenario 13**	1332750	1326555
Scenario 4	1322224	1312069	**Scenario 14**	1342522	1333199
Scenario 5	1568880	1559468	**Scenario 15**	1279457	1265622
Scenario 6	1578483	1568220	**Scenario 16**	1282836	1263142
Scenario 7	1352147	1315341	**Scenario 17**	962546.9	959718.6
Scenario 8	1165159	1158724	**Scenario 18**	1330617	1325639
Scenario 9	1112058	1108010	**Scenario19**	1277980	1268351
Scenario 10	1424255	1420819	**Scenario 20**	1464376	1452778

management model, i.e. $\omega_{price}=1$ in Eq. (25). The results of this case can be seen from Table 1. The specified conditions similar to case I-B would be desired when demand response programs and demand elasticity to market price variation is intended for the market entities. In simple words, the risk management related to the price uncertainty has profitable consequences in the economical analysis of market trader from the viewpoint of financial business risk.

Case I-C: $\omega_{wf}=0.5$, $\omega_{price}=0.5$

Finally, case I-C indicates a risk constrained model for hybrid generation system (hydro-wind GENCO) management with the same importance weight for risk investigation of energy/reserve prices and wind power uncertainties.

In fact, the proposed multi-target risk indices, i.e. Eq. (25), can be used as the upper bound for total acceptable loss of profits that is expected and adjusted by GENCOs. Different values of risk assessment weights (ω_{wf}, ω_{price}) provide comprehensive risk management tool depending on GENCO's objectives. The target profit value and maximum expected downside risk (profit loss) which are considered in case I, are listed in Table 3 for three mentioned sub-cases. The proposed risk management model of hybrid generation system is carried out with respect to the results in Table 3. Table 4 shows total profits of GENCO in each scenario considering $\alpha=20\%$ as the allowable profit loss tolerance.

According to the first part of Eq. (25), the hourly target profit of WHPS program in the sub-cases A, B and C are equal to \$1263895, \$1200885 and \$1232390, respectively. These target values imply to minimum profit of financial business that GENCO should gain during hourly activity.

The reported profits of WHPS for any given scenario in Table 4, which is a function of different risk weights in each sub-case, are relatively different from those results which are given in Table 2 for the base cases. Accordingly, because of the impact of risk constraints in WHPS, the profit value has reduced in many scenarios. Regarding to the maximum amount of the expected downside profit loss (risk), the GENCO faces with financial constraint during daily generation scheduling and has to adjust its operational program in order to satisfy allowable profit loss tolerance limit. The highlighted results in Table 4 determine violated scenarios which their total profit value is less than the target profit (in each sub-cases) and GENCO's owner has suffered financial loss. The maximum profit loss in comparison with the target profit and EDR^{max} in each sub-cases of case I is \$391206 for case I-A, \$343507 for case I-B and \$327480 for case I-C that all happened in scenario 19.

5.3. Case II: $\alpha=10\%$ as the maximum profit loss tolerance

The proposed risk constrained model of wind/hydro generation scheduling is carried out in the case II considering $\alpha=10\%$ as the maximum risk tolerance of GENCO activities. Regarding to the reduction of acceptable value of risk tolerance, GENCO faces with financial constraint and does not have quite free authority to schedule its operational programs. In order to see the effects of the uncertain parameter weighting on the EDR^{max} value and its impact on the results of risk constrained WHPS, three different sub-cases considering various risk weights are considered in the case II similar to case I. The target profit value and maximum expected downside risk (profit loss) of the case II are listed in Table 5 for the following sub-cases.

Case II-A: Highest weight for the wind power uncertainty considering $\alpha=10\%$.

Case II-B: Highest weight for the market price uncertainty considering $\alpha=10\%$.

Case II-C: Same risk weights for both uncertain market price and wind power considering $\alpha=10\%$.

Based on the values of target profit and EDR^{max} in Table 5, the WHPS program considering risk constraints is performed for case II. Profit results in each scenario regarding to various risk weights are shown in Table 6. As it can be seen from this table, the total profit loss has a decreasing trend in comparison with the results of case I. Number of violated scenarios from the profit loss point of view are 8, 4 and 6 scenarios (bold numbers in Table 6) in case II-A, case II-B and case II-C, respectively. Total profit loss of mentioned scenarios in three sub-cases are equal to \$54651.9 for case II-A, \$34175.1 for case II-B and \$45225.8 for case II-C. Despite the overall profit loss related to the violated scenarios in three sub-cases of case II, the total scenario profits in case I are greater than case II. This matter is caused by reducing the maximum profit loss tolerance which leads to GENCO pursue more conservative bidding strategies with respect to the uncertain parameters and their effects on financial business risk. Final comparison between total scenario profits is given in Table 7 after discussion on the results of the case II. Table 7 provides a summary of the GENCO's net revenue and lost profits in two base cases (WHPS without risk constraint) and two risk constrained cases. As it can be clearly inferred from the reported results in Table 7, the expected profit of the total selected scenarios has a deceasing trend with respect to the decrement in the profit loss tolerance.

For example, the value of the expected profits in sub-case A is \$1273106 in case I. However, despite the 50% reduction in the

Table 3
Target profit and maximum EDR of risk constrained model, Case I.

	$TARGET_{Profit}$ (\$/h)	EDR^{max} (\$)
Case I-A	1263895	140772
Case I-B	1200885	146202
Case I-C	1232390	143487

Table 5
Target profit and maximum EDR of risk constrained model for Case II.

	$TARGET_{Profit}$ (\$/h)	EDR^{max} (\$)
Case II-A	1263895	70386
Case II-B	1200885	73101
Case II-C	1232390	71743

Table 4
Total scenario profit of GENCO with risk constraints, Case I.

	Case I-A	Case I-B	Case I-C		Case I-A	Case I-B	Case I-C
Scenario 1	**1255957**	1318110	1365401	**Scenario 11**	1447909	1422124	1449505
Scenario 2	1448089	1431529	1447930	**Scenario 12**	1381175	1371866	1377389
Scenario 3	1477945	1459612	1478089	**Scenario 13**	**1237615**	1257980	1270762
Scenario 4	**1221417**	1251291	**1230248**	**Scenario 14**	**1220382**	1242874	1260786
Scenario 5	1472987	1455313	1473266	**Scenario 15**	**1180476**	**1153274**	**1172260**
Scenario 6	1481573	1462299	1482714	**Scenario 16**	1270622	**1162419**	1268224
Scenario 7	1270004	1200885	1269239	**Scenario 17**	**872689.4**	**857378**	**904910.5**
Scenario 8	**1066903**	**1053008**	**1087999**	**Scenario 18**	**1189467**	1220118	1239345
Scenario 9	**1025460**	**1036254**	**1044515**	**Scenario 19**	1287304	1269223	**1087305**
Scenario 10	1337718	1331266	1336939	**Scenario 20**	1394740	1352959	1375262

allowable risk index from case I to case II (α = 20%–α = 10%), this value reaches to $1266950 which has the significant reduction in GENCO's profit. Also, similar condition can be observed from other corresponding sub-cases between different cases. Numbers of scenarios with less earned profit than the target profit which are highlighted in Tables 4 and 6 and loss of variable profit has also decreased while the allowable risk tolerance is reduced. In addition to the aforementioned points, there is one important note in the proposed risk management model from the risk assessment weighting viewpoint. During those sub-cases that uncertainty impact of wind power has higher weight in the expected risk index (EDR) measurement (for instance case I-A in comparison with case I-B), GENCO faces with higher rate of profit loss. This issue implies that the wind power generation is weather condition dependent and GENCO owner is restricted by the natural constraints. In simple words, impacts of wind power generation uncertainty is a substantial concern in GENCO financial activities and should be exactly quantified during the generation risk measurement and management model.

Detailed comparison of the total expected profits between different risk constrained cases is depicted in Figs. 6–8. Comparison of these figures shows lower value of the allowable profit loss tolerance (α%) which would reduce the scenario profits in different sub-cases. This reduced profit can be assessed with the height of profit columns than the target profit that is remarked by the black horizontal line in mentioned figures. However, this direct relationship (profit reduction versus lower acceptable risk tolerance) can be observed in most of the scenarios. There are several scenarios in Figs. 6–8 that do not follow this trend. For example in scenarios 4, 8, 9 and 17 it can be clearly observed, the value of WHPS profit deceases with reduction of acceptable risk tolerance. Main cause of this issue is that despite the inclusion of risk constraints in WHPS, GENCO faces with some inevitable natural restrictions such as the stochastic wind speed behavior and power generation trend that affect the total expected profits. In order to have better analysis, the comparison between the total wind power generation in the selected scenarios from Table 1 and following figures, demonstrates scenarios with the reduced profit due to the higher amount of risk index having lower value of wind power generation (i.e. scenarios 4, 8, 9 and 17).

6. Conclusions

This paper considered a practical methodology of risk measurement and management model for hybrid wind/hydro generation scheduling that allows GENCO to manage the risk of wind generation and market price uncertainties in the day-ahead energy/reserve market. The proposed risk constrained market model is based on the optimization procedure for the maximization of the expected profits in the presence of risk constraints considering novel weighted risk coefficients as maximum expected downside risk. The risks associated with the stochastic resources and uncertain market price are weighted in the different sub-cases under various amount of allowable risk tolerance and the proposed risk constrained WHPS model is investigated for each cases. The reported results demonstrate that the expected net profits and profit loss due to the risk constraint would be different depending on the importance coefficient of the considered uncertain parameters. As seen in the present work, when importance weight of wind generation uncertainty increases during WHPS risk management model, GENCO might confront with unexpected profit tolerance which has to be exactly investigated by GENCO's owner in practical cases. With application of the proposed risk constrained WHPS market model, GENCO is able to adopt different risk-control bidding strategies to gain acceptable benefit/risk trade-off between the expected benefits of financial activities and how much risk it is willing to assume.

Table 7
Summary of WHPS results for two base case and risk constrained cases.

	Expected profit ($) $\sum_s p^{norm}(s)PROFI(s)$	**Number of violated scenario**	**Loss of total profit** ($)	EDR^{max} ($)
Base case A	1357373	–	–	–
Base case B	1346119	–	–	–
Case I-A	1273106	9	−59369	140772
Case I-B	1262058	5	−41593.2	146202
Case I-C	1279696	6	−48469.7	143487
Case II-A	1266950	8	−54651.9	70386
Case II-B	1252239	4	−34175.1	73101
Case II-C	1270459	6	−45225.8	71743

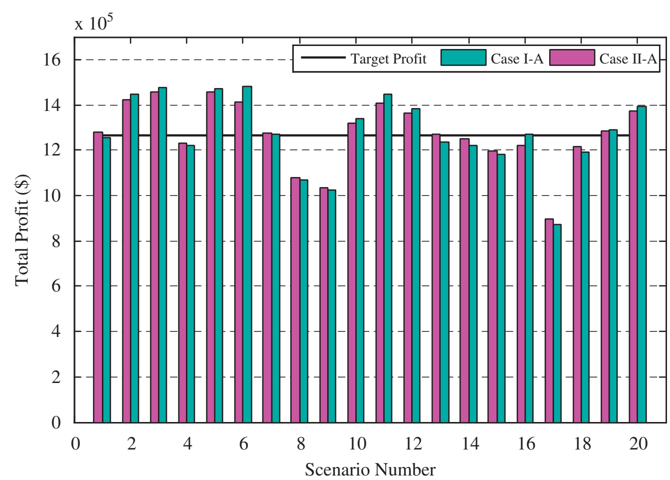

Fig. 6. Comparison between the profit results of sub-case A in the risk constrained WHPS cases.

Table 6
Total scenario profit of GENCO with risk constraints, Case II.

	Case II-A	**Case II-B**	**Case II-C**		**Case II-A**	**Case II-B**	**Case II-C**
Scenario 1	1280631	1298736	1347515	**Scenario 11**	1409702	1414063	1435134
Scenario 2	1423779	1407497	1433265	**Scenario 12**	1363621	1354430	1361897
Scenario 3	1458231	1440143	1463367	**Scenario 13**	1269613	1246092	1254075
Scenario 4	**1230714**	1221792	1242689	**Scenario 14**	**1252483**	1235084	**1228264**
Scenario 5	1458441	1420942	1458612	**Scenario 15**	**1197791**	**1180665**	**1193551**
Scenario 6	1410600	1391859	1437828	**Scenario 16**	**1221095**	1242061	1256733
Scenario 7	1272598	1203338	1256509	**Scenario 17**	**894613.2**	**869349.3**	**898209.1**
Scenario 8	**1079627**	**1067767**	**1072515**	**Scenario 18**	**1213848**	1224616	1236847
Scenario 9	**1032371**	**1024852**	**1034954**	**Scenario 19**	1283478	1225461	**1176244**
Scenario 10	1320816	1314445	1323654	**Scenario 20**	1374064	1342452	1363848

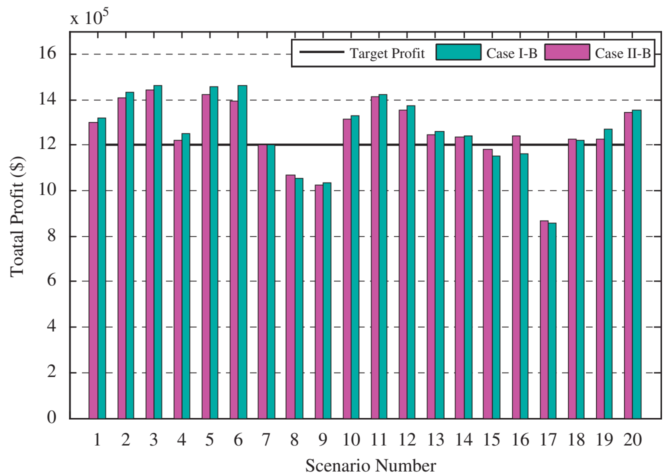

Fig. 7. Comparison between the profit results of sub-case B in the risk constrained WHPS cases.

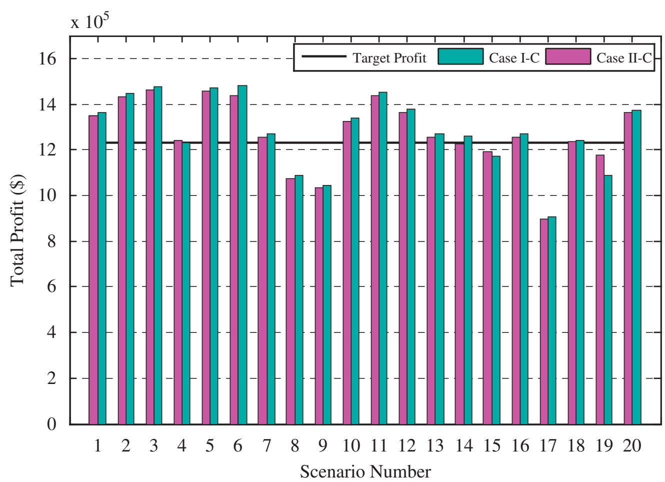

Fig. 8. Comparison between the profit results of sub-case C in the risk constrained WHPS cases.

Appendix I

Auto and cross correlation coefficients related to two implemented wind farms [30]:

$$\theta_1 = \begin{bmatrix} \theta_{11} & \theta_{12} \\ \theta_{21} & \theta_{22} \end{bmatrix} = \begin{bmatrix} -0.15 & -0.04 \\ -0.44 & 0.22 \end{bmatrix}$$

$$\theta_0 = \begin{bmatrix} \theta_{0,1} \\ \theta_{0,2} \end{bmatrix} = \begin{bmatrix} 0.008 \\ 0.007 \end{bmatrix}$$

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